Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.7 n.30, p. 29-36. Jul/Aug, 2021

DOI: https://doi.org/10.5935/jetia.v7i30.768

RESEARCH ARTICLE OPEN ACCESS

DETECTION OF PLANT LEAF DISEASES USING RECENT PROGRESS IN DEEP LEARNING-BASED IDENTIFICATION TECHNIQUES

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ARTICLE INFO

Article History
Received: August 06th, 2021
Accepted: August 23th, 2021
Published: August 31th, 2021

Keywords:
Plant Leaf Diseases Detection,
Deep Learning Models,
Image Processing,
AlexNet,
GoogleNet.

ABSTRACT

Mostly economy profoundly depends on farming efficiency. The farming crops are commonly affected by the disease. Since the economy depends on agriculture, this is one of the core reasons that infection identification in plants assumes a significant job in the horticulture field. On the off chance that legitimate consideration isn't taken here, at that point, it causes natural consequences for plants and because of which particular item quality, amount, or efficiency are influence. Crop misfortune because of ailments considerably influences the economy and undermines food accessibility. Quick and precise plant ailment location is essential to expanding farming efficiency in a supportable manner. In any case, plant location by human specialists is costly, tedious, and sometimes unrealistic. To counter these difficulties, Plant pathologists want an exact and dependable plant sickness conclusion framework. The on-going utilization of deep learning procedure with image processing methods for plant sickness acknowledgment has become a hot examination subject to give programmed analysis. This research provides a productive plant illness distinguishing proof technique dependent on pre-prepared deep learning models, such as AlexNet and GoogleNet designs. We trust that this work will be a significant asset for analysts in the area of ailment acknowledgment utilizing image handling strategies with deep learning architectures.

I. INTRODUCTION

In India, tomatoes and potatoes are the significant crop plant after the main crops such as rice and wheat. Leaf blight and bacterial spot are the most predominant maladies of the tomatoes and potatoes. Plant infections have consistently been a noteworthy worry in agribusiness since they cause a decrease in crop quality. The crop plant diseases might make generous monetary misfortunes since the rural Indian economy exceptionally based on agricultural productivity efficiency. The impacts of plant ailments extend from minor manifestations to the genuine harm of whole zones of planted harvests, which causes major budgetary expenses and effects vigorously on the horticultural economy, particularly in creating nations [1]. If these maladies distinguish at an underlying stage and therapeutic measures take at that starting point, crop yield and grain quality might be protected. At the beginning phase, the side effects of plant diseases show on various pieces of infected plants, especially leaves, in terms of perceptible change in shading and spots. To distinguish a plant malady in the starting stage, utilization of the programmed illness identification method is useful. In this manner, there is an incredible interest in exact recognizable proof strategies for plant leaf maladies.

The current strategy for plant malady recognition is by eye perception of specialists through which distinguishing proof and discovery of plant sicknesses [2]. In doing so, a large group of specialists just as constant observing of the plant requires, which costs extremely high when doing with vast ranches of area. In such conditions, the proposed automatic plant leaf disease strategy ends up being valuable in checking vast fields of yields. Automatically recognizing the plant's weaknesses by merely spotting the side effects on the crop leaves makes it more straightforward and less expensive. Plant sickness by expert's visual way is more relentless assignment and, at the same time, less precise and should be conceivable just in reserved zones. If an automatic recognition procedure utilizes, it will take fewer endeavors, less time, and become more accurate. In the new era, machine learning strategies have gained some attention in leaf malady detection [3]. The machine learning-based strategies have been fruitful in recognizable proof of plant diseases. Different explores such as neural network and support vector machine algorithms have occurred under the field of machine learning for plant malady location detection.

Upgrades in machine learning procedures lately have made them the best in class among different computer vision approaches for image processing applications. A deep learning strategy is another pattern in the artificial intelligence-based machine learning approach, and it accomplishes best in image classification fields. Deep learning empowers the immediate utilization of crude information without utilizing carefully assembled highlight features [4]. A customary machine learning-based computer vision tactic for crop illness identification requires manual determination of characteristics. Interestingly, profound deep learning strategy based convolutional neural systems naturally learn the most significant feature highlights by multilayer [5-6]. So deep learning-based mechanized location procedures gives an open door in the field of accuracy farming. Preparing a deep convolution neural system requires a gigantic measure of information and elite processing assets. The primary point of the deep learning technique is successfully distinguishing the sickness of a plant leaf and improves the acknowledgment rate [7-8]. In the deep learning strategy, there are lots of pre-trained models presented, such as CNN, AlexNet, GoogleNet, and so on. Some of the existing research related to plant disease recognition shown in Table 1.

Table 1: Existing research related to plant diseases recognition.

S. No	Author and Year	Model name	Comments
1.	Mrunalini R Badnakhe, 2011 [5]	K-means clustering algorithm	Neural network use the K-means clustering algorithm for plant diseases recognition. Accuracy level can increase.
2.	Kulkarni Anand H, Ashwin Patil RK,2012 [6]	Artificial Neural Network	Artificial Neural Network used for classification with the Gabor filter based feature extraction. Recognition level can better.
3.	Arivazhagan S, Newlin Ananthi S , 2013 [7]	Support Vector Machine	Support Vector Machine used for classification. The dataset amount can be increased.
4.	Amara, J.; Bouaziz, B.; Algergawy, A, 2017[8]	Modified LeNet	CNN based Modified LeNet used for recognition. Error rate can be reduce.
5.	Cruz, A.C.; Luvisi, A.; De Bellis, L.; Ampatzidis, 2017[9]	Modified LeNet	CNN based Modified LeNet used for recognition. Accuracy rate can be increase.

Source: Authors, (2021).

This research paper's principal goal is to manage the food productivity by earlier observing of crop health like leaf symptoms. The vital aim is to generate an automatic deep learning-based crop disease detection system. This paper deliberates on Alexnet and GoogleNet based model for healthy and defected leaf classification. Generally, out-dated machine learning-based image classification includes preprocessing, segmentation, highlighted feature information extraction and classification. But advanced, deep learning approach includes preprocessing, segmentation, and grouping with automatic feature extraction.

II. MATERIAL AND METHODS

II.1 DATASET

This work uses the PlantVillage dataset, which consists of 15 different plant classes with the images of pepper bell, tomato, and potato diseases. The PlantVillage dataset includes leaf disease image samples for disease identification. This dataset contains approximately 3700 samples and which is freely available. This research selected the image of the pepper bell, tomato, and potato leaves from the data set for analysis [9]. The pepper bell leaf dataset was composed of symptom images of healthy pepper bell leaf and pepper bell leaf bacterial spot. The potato leaf dataset was composed of symptom images of healthy potato leaf, potato early blight and potato Late blight affected leaf [10]. The tomato dataset contains healthy leaf image with target spot affected leaf, mosaic virus affected leaf, yellow leaf curl virus affected leaf, bacterial spot affected leaf, early and late blight affected leaf, spot affected leaf, spider mites, and two-spotted spider mite disease affected leaf images. In this paper, each class utilizes the 200 e samples for each category. Some of the corresponding images show in Figure 1.

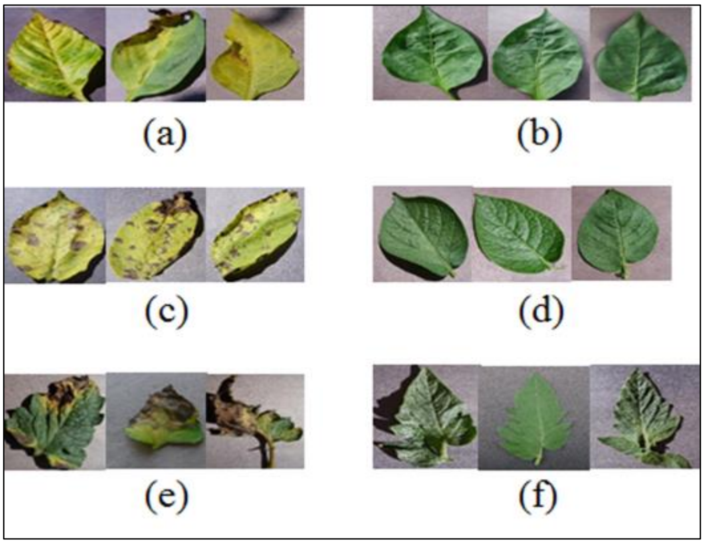


Figure 1: (a) Pepper bell Bacterial spot (b) Pepper bell healthy (c) Potato early blight (d)Potato healthy (e) Tomato Early blight (f) Tomato healthy.
Source: Authors, (2021).

II.2 BACKGROUND

CNN generally utilizes deep learning models in taking care of pictures related to assignments like identification, detection, classification, and so on [11-13]. These systems commonly blend convolution layers, pooling layers, and completely associated (fully connected) layers. These three squares utilize to build a CNN model by changing the number of layers, including or erasing a layer. CNN picture classification takes an information picture as input, processes it, and characterizes it under specific classes (Example: healthy leaf and disease affected leaf). When using Deep learning-based CNN models to train and test, each informative image samples will go through a progression of convolution layers with channels (Kernals), pooling, completely associated layers (FC). Finally applies to Softmax capacity to arrange an item with probabilistic qualities somewhere in the assortment of zero and one [14].

Convolution is the first layer to extricate highlight feature information from an input sample image. Convolution saves the association between pixel values by learning image feature highlights utilizing little squares of information. The pooling layers segment would diminish the number of boundaries when the image samples are excessively huge [15]. Spatial pooling, also called subsampling or downsampling, reduces each guide's dimensionality yet holds essential data. The layer called as FC layer straightened the grid into the vector and fed it into a wholly associated layer like a neural system. Different models have created since 2012 Imagenet rivalry, which had decreased the misclassification rate from 15.6% to 3.7% more than four years. Every model had shifting hyper boundaries or had utilized new strategies like Drop out, Image augmentation, regularization, normalization, Batch standardization, and so on. In this research, the plant disease classification model is using the AlexNet and GoogleNet model [16-18].

II.3 ALEXNET

Even though CNN based, LeNet was notable in the PC vision and AI model group, which accomplished excellent outcomes on new little datasets. The presentation and practicality of preparing convolutional systems on more significant, more sensible datasets still couldn't seem set up. AlexNet is one of the CNN based models for image characterization. It broadly won the 2012 ImageNet LSVRC-2012 rivalry by a large margin in second place with 15.3% VS 26.2% error rates [Krizhevsky et al., 2012]. The structures of AlexNet and LeNet are fundamentally the same. AlexNet utilized an 8-layer convolutional neural system. This system demonstrated that just because the feature highlights got by learning can rise above physical configuration feature highlights, breaking the past worldview in PC vision [19].

Even though the AlexNet system had a fundamentally the same as design as LeNet, however, was more profound with more channels per layer, and with stacked convolutional layers. It comprises 11×11, 5×5, 3×3, convolutions, max pooling, dropout, information expansion technique by image augmentation, ReLU activations, and SGD with momentum. It joined the ReLU function after each convolutional and completely associated fully connected layer. In AlexNet's first layer, the convolution window shape is 11×11. Subsequently, a bigger convolution window expects to catch the item. The convolution window shape in the subsequent layer is diminished to 5×5, trailed by 3×3. Likewise, after the principal, second, and fifth convolutional layers, the system includes the most significant pooling layers with a window state of 3×3 and a stride of 2. Additionally, AlexNet has multiple times more convolution channels than LeNet.

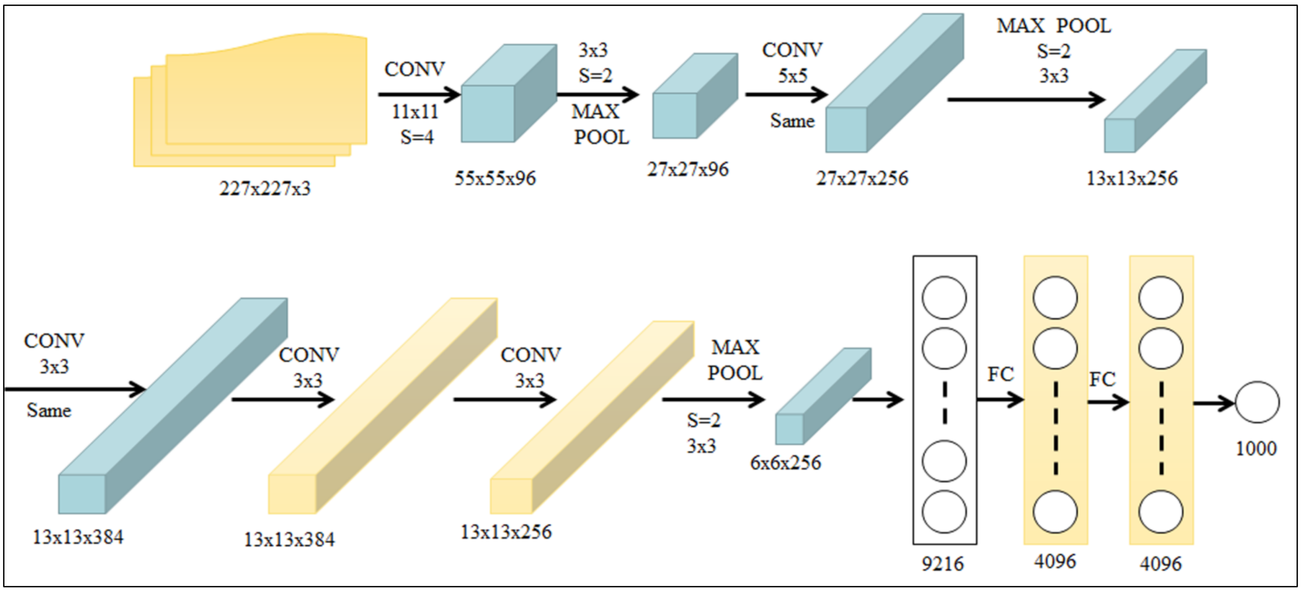


Figure 2: AlexNet architecture.
Source: [10].

After the last convolutional layer, there are two wholly associated FC layers with 4096 yields. These two gigantic completely associated layers produce model parameters of about 1 GB. AlexNet changed the sigmoid function to a more accessible ReLU initiation work. From one perspective, the calculation of the ReLU enactment work is more straightforward [20-22]. For instance, it doesn't have the exponentiation activity found in the sigmoid activation work. Relu actuation work utilizes rather than Tanh to include non-linearity. It quickens the speed by multiple times at a similar exactness. The AlexNet model uses dropout rather than regularization to manage to overfit. Be that as it may, the preparation time multiplies with the dropout pace of 0.5. It decreases the top 1 and top-5 mistake rates by 0.4% and 0.3%, individually. The AlexNet model display in Figure 2.

II.4 GOOGLENET

GoogLeNet is the victor of the ILSVRC 2014, an image characterization rivalry, which has vast improvement over LeNet and AlexNet deep learning models and has a moderately lower mistake rate contrasted than the VGGNet. GoogLeNet is from Google. It additionally called as Inception v1 model. It contains 1×1 convolution at the center of the system. Global pooling also utilizes toward the finish of the system as opposed to using completely associated FC layers. Another strategy used in the GoogleNet model, called the inception module, is to have various sizes/sorts of convolutions for similar information and to stack all the yields. In GoogLeNet, 1×1 convolution is utilized as a measurement decrease module to lessen the calculation. Already, completely associated (FC) layers are used toward the end of the system, for example, in AlexNet. In GoogLeNet, global pooling utilizes toward the end of the system by averaging each component map from 7×7 to 1×1. The model found that a move from FC layers to average pooling improved the top-1 accuracy by about 0.6%. There are 22 layers altogether.

It is now a profound model contrasted and past AlexNet, ZFNet, and VGGNet. Furthermore, can see that there are various inception modules associated together to go further. There are some transitional softmax branches at the center. On the off chance that a system workes with numerous profound layers, it may confront overfitting. To tackle this issue, going further with convolutions idea is proposed the GoogleNet engineering with having channels with different sizes that can work on a similar level [23]. With this thought, the system becomes more extensive as opposed to more profound. A maximum pooling activity is likewise performed with the convolutions and then sent into the following inception module. Since neural systems are tedious and costly to prepare, an extra (1 × 1) convolution used before the (3 × 3) and (5 × 5) convolutions to diminish the elements of the system and perform quick calculations. The GoogleNet model appears in Figure 3.

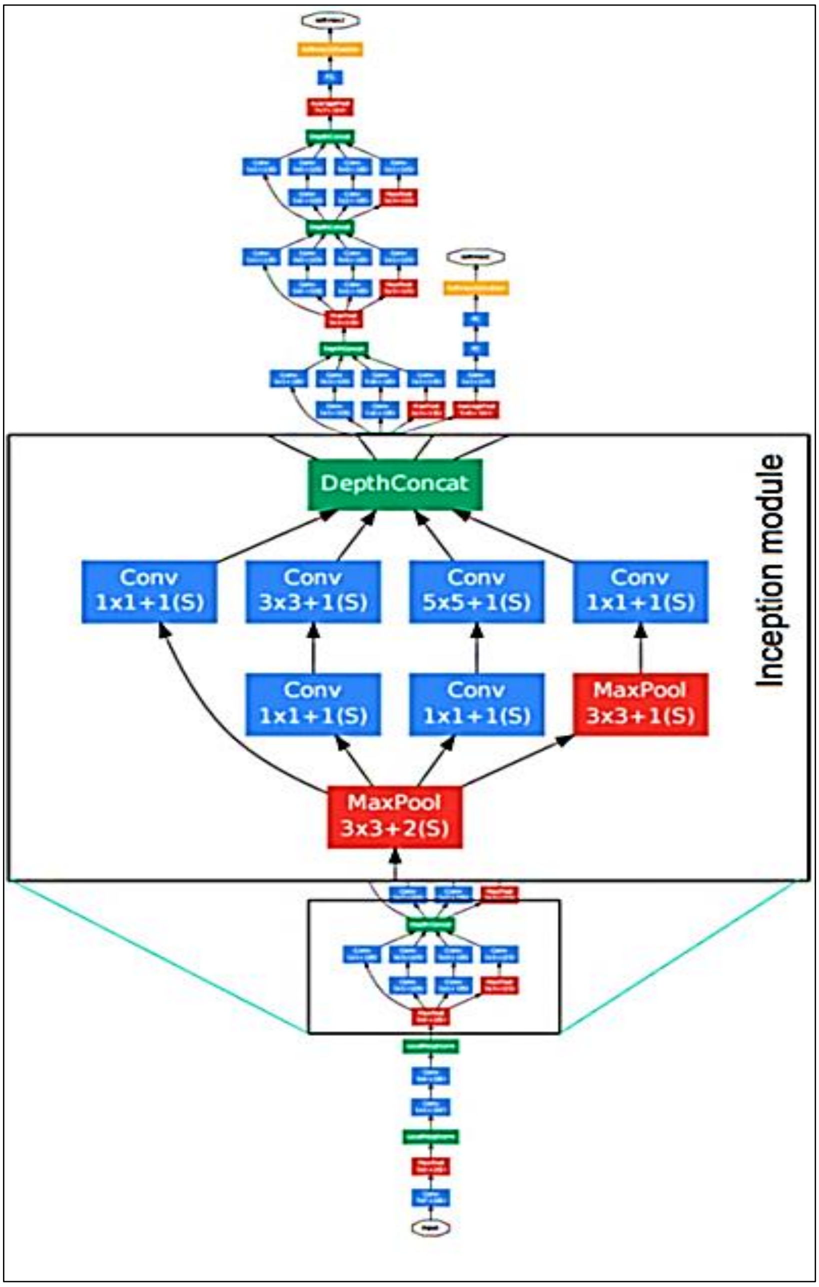


Figure 3: GoogleNet architecture.
Source: [11].

III. EXPERIMENTAL SETUP

The proposed research work utilized the AlexNet and GoogleNet pre-prepared model for plant leaf sicknesses recognizable proof. The plant village dataset isolates into the train, validate and test plant samples. In this exploratory arrangement, all the 15 classes utilize, where each class has around 200 examples. An aggregate of nearly 3,700 samples was available in the dataset, which was part of the train and valid samples during the run time on 80:20 proportions. For preparing and testing the neural systems, Keras consider as a deep learning structure with Tensorflow as a backend. The whole preparation and testing performed on a Windows 64-piece work area PC. The training sets are going into the pre-preparing step, such as resizing, noise removal, etc. As indicated by the information appropriation of the train set and test set idea, the plant town preparing dataset incorporates the picture expansion process. Likewise, the plant village dataset is in uneven condition. This paper utilized random translation, cropping for information upgrades during the training process, to reduce the possibility of overfitting [24].

The initial learning rate for leaf illnesses identification is 0.001. The proposed ailment discovery model improves with the assistance of Adam analyzer with the loss of cross-entropy [25]. A few hyper boundaries are required to run the proposed model; Diverse hyper boundaries, such as padding, strides, and channels, are utilized at every one of the layers that could be tuned to manufacture a superior model. This arranged model used Xavier's initialization for weight introduction for the training process. This examination work runs the investigation up to 30 epochs to accomplish the best outcome model [26]. Diverse batch sizes tested; however, a notable volume of 32 utilizes for the training process. The arranged model gives in Figure 4.

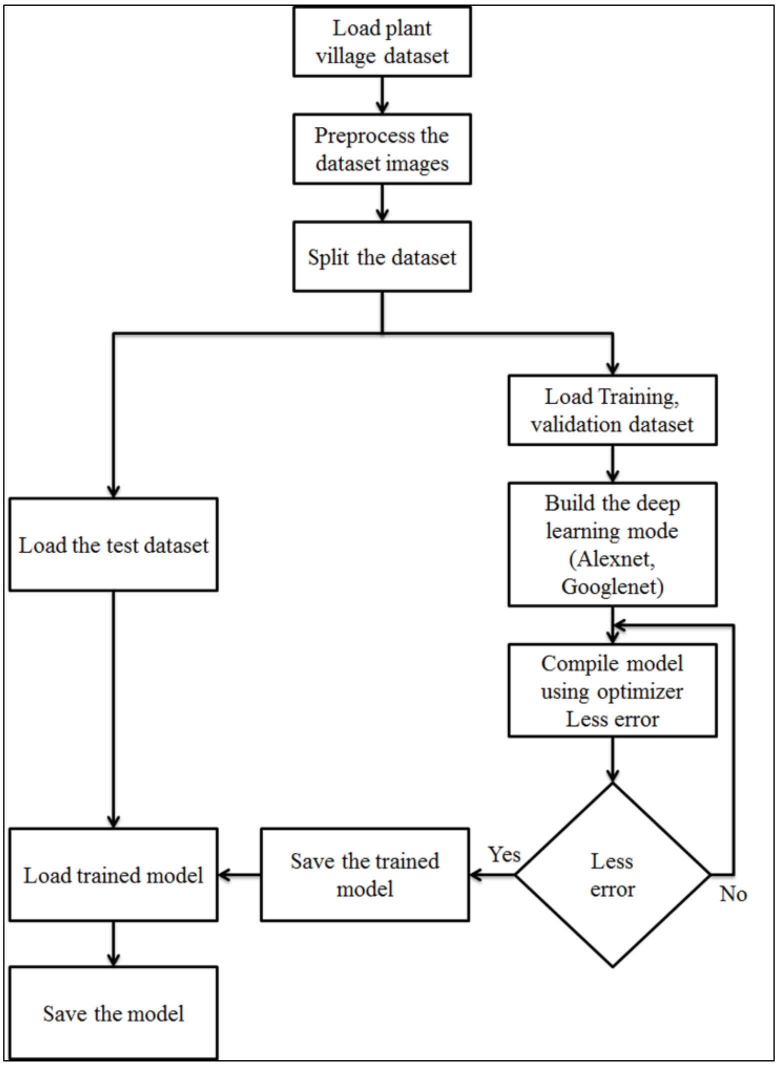


Figure 4: Experimental model design.
Source: Authors, (2021).

The model trains with the planned hyperparameter features such as learning rate, optimizers, epochs, and batch size. The arranged examination has utilized Adam enhancer with a learning rate of 0.001. When the model arranges, the pre-prepared dataset enters into the model [27]. The preparation accomplishes 30 epochs after every epoch approval done on the validation part, in the development of tuning the hyperparameter boundaries for different quantities of channels, batch size, and the last model with ideal precision spares. The spared model utilizes for testing new information that is not found in the train and test set. During fine-tuning, fluctuated learning rates apply for the model [28-29]. After the training process, the model assesses with the probabilities that each sample has a place with a particular class was determined.

IV. RESULT AND DISCUSSION

In this paper, the utilization of Deep Convolutional Neural Networks has detail architecture to detect ailment on leaf image. The proposed philosophy tries on 15 classes of three kinds of yields. The exploratory outcomes show that the GoogleNet model performs better than the AlexNet model as far as exactness and loss value. The training and validation based precision, loss value esteem for AlexNet, and GoogleNet show in Figure5. From the outcomes, it tends to see that lone not many examples leave misclassifies. So the proposed model is prepared legitimately with appropriate hyperparameter boundary esteems.

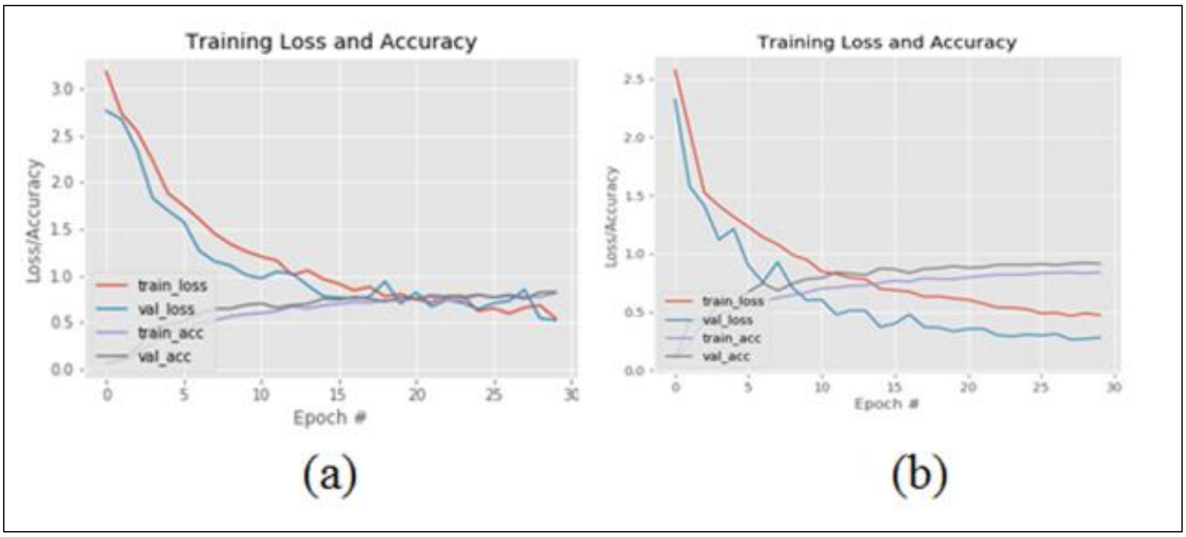
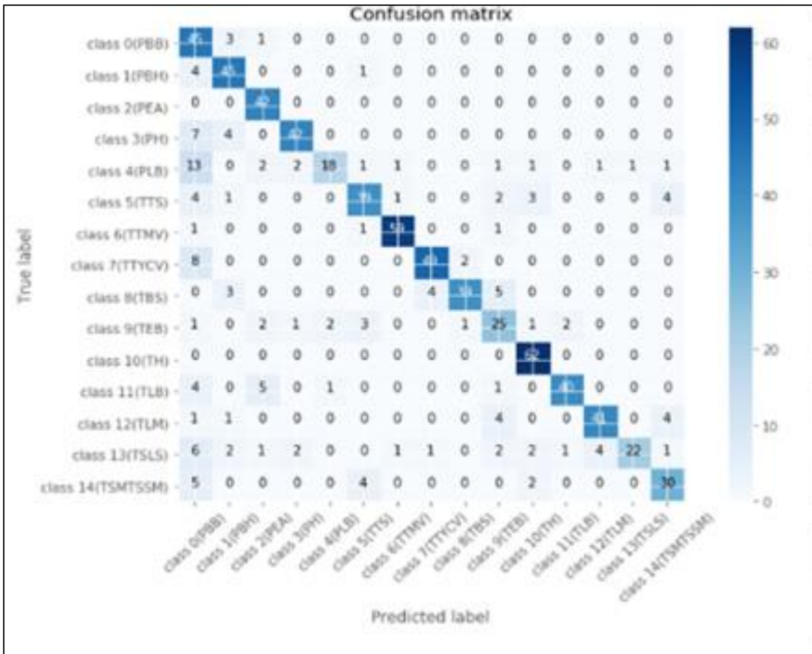


Figure 5: Training and validataion result (a) AlexNet (b) GoogleNet
Source: Authors, (2021).

In this area, results, and perceptions of the experimentation performed on both models reference. If there should be an occurrence of testing for the discovery of harvest infection, according to Figure 5, both AlexNet and GoogleNet models perform well with 83.62% and 85.74% exactness separately. A noteworthy development inexactness shows in starting stages that get met at convergence later on. Exponential drop in loss work indicates that quicker learning in the underlying stage. It suggests that the GoogleNet model performs better than AlexNet in the assignment of yield identification.



Class 0 (PBB)	**Pepper__bell___Bacterial_spot**
Class 1 (PBH)	Pepper__bell___healthy
Class 2 (PEA)	Potato___Early_blight
Class 3 (PH)	Potato___healthy
Class 4 (PLB)	Potato___Late_blight
Class 5 (TTS)	Tomato__Target_Spot
Class 6 (TTMV)	Tomato__Tomato_mosaic_ virus
Class 7 (TTCV)	Tomato__Tomato_Yellow Leaf__Curl_Virus
Class 8 (TBS)	Tomato_Bacterial_spot
Class 9 (TEB)	Tomato_Early_blight
Class 10 (TH)	Tomato_healthy
Class 11 (TLB)	Tomato_Late_blight
Class 12 (TLM)	Tomato_Leaf_Mold
Class 13 (TSLS)	Tomato_Septoria_leaf_spot
Class 14 (TSMTSSM)	Tomato_Spider_mites_Two_spotted_spider_mite

Figure 6: Confusion matrix.
Source: Authors, (2021).

The proposed model's planned architecture gave 84.37% training based precision and 82.3% validation based exactness, which unmistakably means the overfitting. So the proposed model actualized scarcely any strategies to defeat the equivalent. One such approach is a dropout, a sort of regularization procedure presented in every one of the convolution layer present in the system, beginning with a likelihood of 0.1 and expanding by 0.1 in each layer. With dropout, the model had the option to lessen the overfitting with a compromise. The test set was feed into the already saved trained model, which gave a test based precision of

81.7%. The confusion matrix framework and test image confirmation for the proposed model appear in Figures 6 and 7.

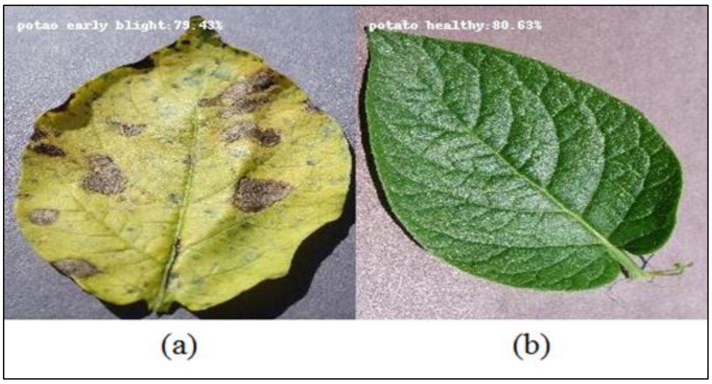


Figure 7. Test image analysis.
Source: Authors, (2021).

V. CONCLUSION

Based on deep convolution models, two models, such as AlexNet and GoogleNet of classification and aim on exactness rate, were proposed to distinguish leaf maladies, including pepper ball, potato, and tomato. Quantitative investigations demonstrated that the above strategies accomplish better acknowledgment results on the unequal informational index, contrasted, and the customary AI-based machine learning-based calculations. The exactness of the proposed techniques on the train based dataset was 83.62% and 85.74% individually. The strategies for this paper could reach out to other plant infection recognizable proof. It recommends that in-plant ailment acknowledgment, the approach proposed in this paper can view as when oversampling and under-sampling can't conquer the effect of data imbalance. Augmentation of this work will incorporate the number of classes of harvests, and its sicknesses can expand.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Jency Rubia J and Babitha Lincy R
Methodology: Jency Rubia J and Babitha Lincy R
Investigation: Jency Rubia J
Discussion of results: Jency Rubia J and Babitha Lincy R
Writing – Original Draft: Babitha Lincy R
Writing – Review and Editing: Jency Rubia J
Resources: Jency Rubia J
Supervision: Jency Rubia J
Approval of the final text: Jency Rubia J and Babitha Lincy R

VII. ACKNOWLEDGMENTS

The authors would like to thank the VLSI & DSP laboratory at M.A.M College of Engineering and Technology for providing a suitable environment & facilities, which was very helpful to us in research.

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